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Research Article

The Impact of Data-Driven Decision-Making on Consumer Dynamics in the International Digital Environment: An Empirical Study Using the 5As Path Model

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Abstract: This study aims to analyze the effect of Data-Driven Decision Making on the dynamics of consumer behavior in the international digital environment by employing the Consumer Journey Model (5As) as a framework for interpreting the development of consumer behavior across its different stages. The study adopts a consumer perspective and conceptualizes Data-Driven Decision Making as a multidimensional variable encompassing data quality, technological infrastructure, data governance, advanced analytics and the behavioral adoption of data-driven practices. The study adopts a descriptive-analytical approach. Data were collected through an electronic questionnaire administered to a sample of consumers in the international digital environment. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the measurement model and examine the direct and sequential structural relationships among the study variables. The findings show that Data-Driven Decision Making has a positive effect on all stages of the 5As model and strengthens the sequential interconnectedness of the digital consumer journey. These findings confirm that data-driven marketing contributes to building an integrated consumer experience that supports engagement, trust and loyalty in international digital markets.

Keywords: Data-Driven Decision Making, Digital Consumer Behavior, 5As Model, PLS-SEM

INTRODUCTION

In recent years, global attention has shifted toward the strategic role of data in reshaping institutional–consumer relationships amid expanding digital technologies. Understanding consumer behavior has become essential for organizational survival, while data-enhanced interaction has shifted organizations from intuition toward analytically grounded decisions.

Although these changes emerged earlier in developed markets, their momentum is increasingly evident. This makes the consumer journey more complex and increases the need for analysis. The As5 model Awareness, Attraction, Ask, Act and Advocate provides a framework for examining consumer interaction across its stages.

Integrating data analytics across the journey helps organizations interpret interaction drivers and identify links between consumer behavior and surrounding market conditions. Data increasingly reshapes attraction, search and comparison, purchasing decisions based on real-time personalized information and recommendations, strengthening the continuity of the overall experience.

Accordingly, this study analyzes the effect of data-driven interaction on As5 journey effectiveness in the international digital environment, using data representing consumer experiences in several countries. It examines how data-supported interaction affects the journey and its potential to strengthen competitiveness during digital transformation.

The study addresses the following main research question:

Main Research Question

To what extent does data-driven decision-making affect consumer behavior dynamics across the stages of the As5 consumer journey in the international digital environment?

Sub-Questions

- How does data-driven decision-making enhance the Awareness and Attraction stages in the international digital environment
- What effect does data-driven decision-making have on the Ask/Search and purchasing Act stages
- To what extent does data-driven decision-making support the Advocate stage and foster consumer loyalty

To address the research questions and guide the study, the following hypotheses were formulated:

Main Hypothesis
H: Data-driven decision-making positively affects consumer dynamics across the stages of the 5As consumer journey in the international digital environment.

Sub-hypotheses by 5As Stages

- **H1:** Data-driven decision-making positively enhances consumers' brand awareness in the international digital environment
- **H2:** Data-driven decision-making positively strengthens consumers' attraction to brands in the international digital environment
- **H3:** Data-driven decision-making positively facilitates consumers' information search and comparison processes in the international digital environment
- **H4:** Data-driven decision-making positively influences consumers' purchase decisions and repurchase intentions in the international digital environment
- **H5:** Data-driven decision-making positively enhances recommendation behaviors and long-term loyalty intentions in the international digital environment

Study Objectives
This study seeks to achieve the following objectives:

- Analyze the effect of data-driven decision-making on consumer dynamics across the stages of the 5As journey in the international digital environment
- Examine causal and reciprocal relationships among organizational factors supporting data-driven decision-making using the DEMATEL method and assess their overall effects on each consumer-journey stage
- Provide practical and strategic insights for organizations on strengthening data-driven decision-making capabilities to improve effectiveness, increase consumer loyalty and gain competitive advantage in the international digital context

Study Significance
The significance of this study lies in its international scope, which captures consumer perspectives on data-driven interaction in the digital environment. As digital marketing and transformation accelerate, data-driven digital interaction has emerged as an effective approach to designing digital experiences. It can reshape organization–consumer interactions, improve targeting accuracy and strengthen persuasion and recommendation mechanisms.

The study also clarifies how such interaction influences consumer behavior across the 5As journey, providing strategic insights for developing personalized digital experiences that enhance competitiveness and support innovation across diverse and changing economic environments.

Literature Review
International Digital Environment: Context of the Shift Toward Data-Driven Decision-Making: In the international digital environment, data-driven decision-making has become central to contemporary business strategies. The development of the Internet of Things has increased data availability and accessibility for decision-making [1]. The growing volume of data has encouraged marketers to employ advanced statistical modeling to analyze complex customer data, including transaction records and unstructured content such as conversations, images, videos and audio from digital and social media. This has expanded the scope of marketing and increased its reliance on analytical capabilities [2].

Modern marketing technologies provide managers with opportunities to collect, interpret and analyze market data, supporting more accurate and effective decisions. However, data volume and complexity make decision-making more difficult, requiring effort and expertise to obtain meaningful interpretations. Continuous market-data flows and dynamic markets also require decisions to be made and reassessed rapidly, alongside a reconsideration of data-driven marketing decision-management practices [3].

Consequently, marketing decision-making has become vital to organizational strategic and operational performance, creating a need for systematic, data-based methods that enable managers to monitor internal and external behaviors, derive accurate insights and guide decisions strategically. This data-enabled approach supports market understanding, adaptation and faster, flexible and effective marketing decisions.

Decision-Making

Theoretical Concept and Application in Marketing: Decision-making theory views this process as identifying, evaluating and selecting available alternatives according to the value associated with each option under conditions of certainty or uncertainty. Individuals are assumed to act fully rationally, consistently maximizing utility based on complete information and logical reasoning [4].

In practice, particularly within complex and dynamic business and marketing environments, behavioral evidence reveals deviations from this idealized model due to cognitive constraints, time pressure and information ambiguity. This has encouraged more realistic models based on bounded rationality and compensatory tools that improve accuracy and efficiency. Data plays an increasingly important role as an objective factor that can reduce human biases, supporting a practical data-driven approach that combines human capabilities with advanced analytical capacities.

Data-Driven Decision-Making

Concept and Applications in Marketing: Data-driven decision-making refers to organizational or individual practices that employ advanced technological and technical methods to collect and analyze internal and external data to improve decisions [5]. It also involves systematic data collection and analysis to support strategic and operational decisions, using predictive analytics to generate actionable insights for planning [6]. In marketing, this approach enables decision-makers to address complex business problems through data mining, processing, analytical models and predictive algorithms using robust empirical evidence rather than intuition, supporting more informed strategic decisions [7]. Integrating consumer preferences, behaviors, campaign performance, social-media, transaction and rating data supports more effective segmentation, targeting, message personalization and pricing through artificial intelligence, machine learning and big-data analytics for enhanced marketing effectiveness [8]. A prominent application is data-driven behavioral targeting, an emerging digital marketing strategy that guides rather than imposes consumer behavior through personalized, dynamic stimuli. It combines personal and website usage data, including social-media data, with analytics, artificial intelligence and smart technologies to shape consumers' choice architecture [9]. Another application collects and analyzes reviews and data from e-commerce platforms to improve product evaluation by extracting implicit and explicit criteria through text mining and double fuzzy numbers. Advanced aggregation functions integrate data interactions with consumer behavior and preferences, enabling objective decisions [10].

In consumer-behavior research, historical and actual behavioral data reveal hidden patterns beyond experience or intuition. Machine learning, statistics and artificial neural networks support predictive models capable of processing noisy, imbalanced and nonlinear data, predicting consumer behavior such as churn probability and classifying consumers by activity levels and future tendencies. This shifts decisions from experience and conjecture toward measurable evidence [11] However, reliability remains a challenge. Combining domain expertise with human involvement helps ensure logical interpretation and reliable, knowledge-based outputs [12].

Finally, data-driven approaches support optimal actions under uncertainty while balancing cost, reliability and environmental impact. Given changing equipment conditions and decision factors, effective frameworks must integrate human expertise with intelligent systems to improve decision accuracy and reliability [13]. Thus, data-driven decision-making has evolved into a practical marketing tool that improves accuracy and responsiveness to consumer behavior.

Advantages of Data-Driven Marketing

In the rapidly digitizing era, data-driven marketing has become a core pillar of contemporary strategies, using data analysis to improve effectiveness and targeting accuracy while creating ethical and operational challenges requiring responsible data use [14].

- Messages to individual preferences, enhancing satisfaction and emotional loyalty
- Customer relationship management: Segmentation and targeted campaigns improve behavioral understanding, conversion and customer retention
- Consumer journey mapping: Real-time touchpoint insights improve the overall experience and enable immediate decisions

- Data-driven decision-making: Identifying patterns, measuring strategy effectiveness and anticipating complexities reduces reliance on intuition
- Shared value creation: Digital platforms involve consumers in innovation, supporting products that better meet their needs

Dimensions of Data-Driven Decision-Making

As information accelerates and digital environments grow more complex, converting raw data into actionable strategic insights has become central to organizational success. Its value depends not only on availability but on effective integration into decision-making systems. Several interrelated dimensions have therefore been identified: strength in one can reinforce others, while deficiencies may limit benefits [15].

- **Data Quality:** Data quality encompasses the accuracy, reliability and integrity of information and its capacity to generate evidence-based insights. High-quality data are authentic, free from manipulation and distortion and collected and processed through rigorous methods. Thus, quality is not merely technical but essential to research credibility and the validity of data-based decisions [16]
- **Data and Technology Infrastructure:** This dimension comprises systems enabling data collection, processing and analysis, including databases, analytical tools, artificial intelligence and digital platforms linking data with stakeholders. It provides timely information, supports pattern analysis and policy simulation and integrates multiple sources, making it essential for effective decisions [17]
- **Data Governance: Data** governance provides the strategic framework for accessing, managing and using data across entities and systems. Unlike operational data management, governance defines roles and responsibilities and aligns practices with standards balancing innovation and value creation. It translates principles such as transparency and digital sovereignty into applicable practices that support efficient, reliable and accountable data-driven decisions [18]. Continuous adaptation also strengthens resilience, responsiveness and alignment with customer needs, enabling early identification of innovation opportunities [19]
- **Data Culture:** This organizational and social dimension reflects awareness of the importance of using data throughout decision-making. Daily practices seek optimal data use while respecting legal and ethical standards and protecting rights. Data culture makes data a strategic enabler of sound decisions and efficiency [20]. It is also linked to digital culture, encompassing thinking, behavior and knowledge shaped by digital technologies, with artificial intelligence acting as a major driver of interaction with digital content [21]
- **Data Literacy:** Data literacy concerns the ability to understand, analyze, interpret and communicate data as decision inputs. It also involves ethical awareness, critical thinking and recognition of data's role in decision-making. It enables decision-makers to assess data quality and relevance, improving decisions and reducing deviations [22]
- **Data Analytics:** Data analytics enables organizations to process diverse environmental datasets from sensors, satellite imagery, interactions, transaction records and experiments. Analytics converts raw data into knowledge by detecting hidden patterns and trends, building predictive models and evaluating alternatives before implementation, supporting proactive decisions, risk management and [23]. It also involves aggregating, processing and storing big data and transforming it into accessible information for decision-making [24]
- **Business Strategy Alignment:** This dimension reflects the dynamic fit between data-driven initiatives, analytical capabilities, digital technologies and strategic objectives. Such alignment turns data and analytics into inputs for strategic and operational decisions consistent with organizational goals rather than isolated knowledge [25]. It also encompasses innovative digital-business concepts that strengthen system interaction, exploit technological capabilities to develop integrated digital business models and enable real-time organizational monitoring [26]

Consumer Behavior Dynamics in the Digital Context

Amid rapid changes in the international digital environment, consumer dynamics refer to continuous changes in consumers' attitudes and behaviors over time. Consumers include individuals who currently interact with an organization or may do so in the future. These changes are shaped by marketing factors and digital and social developments, making their understanding essential for effective business decisions [27]. Consumer dynamics are evident in evolving preferences and purchasing responses, particularly in markets characterized by innovation and improving product attributes. Contemporary purchase decisions depend not only on characteristics and prices but also on expectations regarding future quality improvements and price reductions. Understanding such dynamics therefore requires temporal rather than static approaches that capture interactions among future expectations, product evolution and behavioral differences [28].

They also emerge from interactions between current consumption and expected future consumption, shaped by learning, accumulated experience and uncertainty. Previous experiences gradually improve prediction and decision control, reinforcing the need for more comprehensive and dynamic analysis of consumer purchasing behavior rather than static assessment [29].

Accordingly, data-driven decision-making enables organizations to monitor changing preferences, identify individual differences and dynamically adapt marketing strategies to actual and expected consumer behavior, improving responsiveness and performance in increasingly competitive digital markets [30]. Modern marketing therefore relies on an integrated, dynamic system of physical and digital efforts to build lasting digital customer relationships, deepen interaction, satisfy needs and generate new desires aligned with organizational strategy [31].

Consumer Purchase Decision Journey Models

Models explaining consumer behavior and decision journeys have received extensive attention in marketing literature because they clarify how consumers interact with brands and respond to marketing messages. One of the earliest is (AIDA), a hierarchical model progressing from attention to interest and desire, then action or purchase, assuming a fixed sequence. It long guided traditional one-way marketing communication. However, its linear structure limits its ability to explain actual behavior, previous experiences, social influences and post-purchase stages such as satisfaction, loyalty and recommendation, prompting the development of models better suited to digital consumer complexity [32]. In response to these limitations, several extensions and alternatives emerged. AIDAR added retention to emphasize post-purchase relationships, while the 4As model proposed Awareness, Attitude, Act and Act Again, with repeated purchasing indicating longer-term customer relationships. The Consumer Decision Journey (CDJ) departed from linear sequencing by integrating consideration, evaluation, purchase, experience, advocacy and engagement [33].

Given the interactive and complex nature of digital environments, a model capable of capturing contemporary consumer relationships and interactions is needed. The 5As consumer journey is therefore adopted for its broader coverage and ability to explain modern marketing dynamics in the digital era.

The 5As Consumer Journey Model

The consumer journey comprises successive stages through which consumers move from recognizing a need to searching for and evaluating alternatives and ultimately selecting a brand or product. It represents a dynamic process reflecting cognitive, emotional and behavioral interactions with the surrounding environment [34]. Another definition views it as a framework dividing the consumer's movement through multiple purchasing decision stages without assuming a fixed or linear sequence. Consumers may skip or revisit stages depending on the product and their level of brand interaction, reflecting the journey's complexity across five stages [35].

- **Awareness Stage:** This initial stage involves acquiring basic knowledge of a brand or product and forming an initial impression. Awareness is commonly assessed through the proportion of the audience familiar with the offering. Higher awareness indicates successful reach through advertising, social-media campaigns and promotions, whereas lower awareness may reflect inaccurate targeting or ineffective communication channels. Awareness establishes the basis for subsequent consumer interest and interaction, supporting the development of lasting relationships and loyalty [36]
- **Attraction Stage:** Attraction stimulates consumer interest and curiosity by presenting distinctive product or brand benefits in compelling ways. Brands employ innovative strategies, including appealing audiovisual content, storytelling and testimonials or recommendations from actual users and influencers, to encourage engagement and emotional involvement while differentiating the brand from competitors [37]
- **Ask Stage:** After interest is established, consumers engage more deeply by searching for and verifying brand or product information through digital and traditional channels. The journey becomes social as consumers rely on external information, including friends' recommendations and other consumers' reviews and experiences, to form a clearer and more reliable basis for purchase decisions [38]
- **Act Stage:** Consumers purchase and initially experience the product or service, assessing its fit with their expectations and needs. Difficulties may lead them to seek customer support, warranties, or demonstrations. This stage allows brands to build trust through effective service and support, whose quality can influence satisfaction, repurchase intentions and subsequent interaction [39]
- **Advocate Stage:** Advocacy extends beyond conventional loyalty based on retention and repurchase. Consumers actively support and promote brands by sharing positive experiences and opinions through digital channels and social networks, potentially influencing prospective buyers. Recommendation, sharing and experience exchange strengthen brand reputation and trust [40]

Empirical Study

This empirical study examines how consumers' perceptions of data-driven decision-making in marketing affect their purchasing behavior dynamics in the international digital environment, using the 5As consumer journey as its analytical framework. It focuses on whether consumers perceive commercial offers, recommendations and marketing interactions across e-commerce websites, social media and global digital marketplaces as outcomes of data-supported analytical strategies rather than random or spontaneous activities. These strategies include predictive algorithms and intelligent models that analyze consumer experiences and behaviors to anticipate preferences. The study therefore examines how awareness of intelligent marketing influences the stages of the 5As journey and consumer interaction and loyalty across borders. The analysis also incorporates the dimensions of data-driven decision-making identified through DEMATEL to examine causal relationships among these dimensions.

Study Sample

The population comprised global consumers who regularly engage in digital shopping. A convenience sample based on simple random selection was recruited through diverse international digital platforms. After excluding invalid responses, the final sample comprised 492 respondents, reflecting broad demographic and geographic diversity and reducing potential bias while providing sufficient statistical power for Partial Least Squares Structural Equation Modeling (SEM-PLS).

Data Collection Instrument

To address the research questions and test the hypotheses, a structured online questionnaire was developed based on the proposed theoretical model. It examined perceived data-driven decision-making as the independent variable and consumer behavior dynamics across the 5As stages as the dependent variable. The questionnaire comprised two main sections and used a five-point Likert scale to measure perceptions and attitudes, enabling quantitative analysis through SEM-PLS to examine causal relationships among variables.

Questionnaire Structure

The questionnaire includes items measuring the study variables, adapted from validated measures in previous literature to fit the research context. It focuses on consumers' perception that digital marketing is data-driven rather than random, e.g., "I notice that the recommendations I receive are based on analysis of my previous behavior (Figure 1)."

Independent Variable

Twenty items assess perceptions of data-driven decision-making across five main DEMATEL dimensions: Data Quality (DQ), Data Infrastructure and Technology (DIT), Data Culture and Governance (DCG), Data Analytical Literacy (DAL) and Business Strategy Alignment (BSA). The items focus on awareness of non-random, data-driven marketing.

Dependent Variable

Twenty items measure consumer behavior dynamics across the 5As model: Awareness (Aware), Attraction (Appeal), Ask, Act and Advocate.

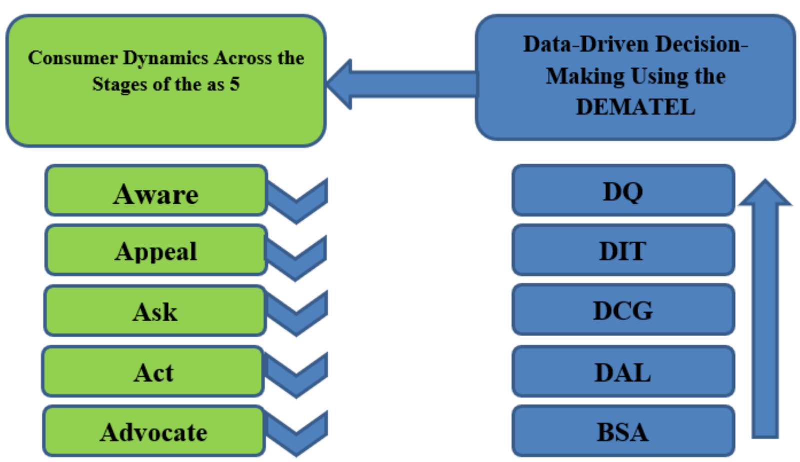

Figure 1: Proposed Research Model
Prepared by the Researchers Based on Previous Studies

The questionnaire was distributed online through digital tools to ensure international reach. This design enables empirical assessment of how consumers’ perceptions of data-driven marketing affect their purchasing journey through the 5As, while linking the findings to DEMATEL causal-dimension analysis, thereby providing theoretical and practical implications for brands in international digital markets.

Descriptive Analysis of Sample Responses to the Study Variables

To identify response patterns for the independent variable, perceived data-driven decision-making and the dependent variable, consumer behavior dynamics based on the 5As model in the international digital environment, means and standard deviations are presented. These measures indicate response dispersion around the mean and characterize the levels of perception and behavior before advanced statistical analysis.

Table 1 shows that all study variables recorded high and closely clustered means, indicating an overall positive perception of data-driven marketing and its influence on purchasing behavior. Relatively low standard deviations also indicate consistency among responses. The Act stage recorded the highest mean, suggesting a stronger data effect on purchase decisions, while Ask had the relatively lowest mean, remaining within the overall positive pattern.

Statistical Analysis

Smart PLS was used to analyze the data through Partial Least Squares Structural Equation Modeling (PLS-SEM), given its suitability for the study and ability to handle complex models. SPSS was used for descriptive analysis.

The methodology assesses the effect of perceived Data-Driven Decision-Making (DDDM) across its dimensions on consumer behavior throughout the 5As model by evaluating the measurement and structural models and testing the research hypotheses. The accompanying figure presents the model structure, relationships among variables and questionnaire items (Figure 2).

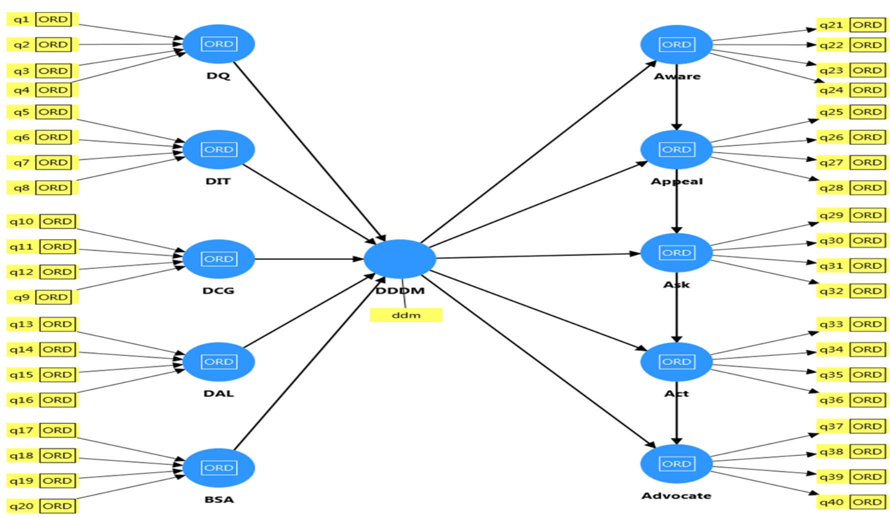

Figure 2: General Model Structure and Relationships Among Variable
Prepared by the Researcher Using Smart PLS v4.1.1.6

Table 1: Sample Respondents’ Responses to the Study Variable

Item	Mean	Std. Deviation
DDDM	3.80	0.571
DQ	3.80	0.716
DIT	3.79	0.696
DCG	3.80	0.720
DAL	3.82	0.690
BSA	3.80	0.709
AsModel	3.81	0.577
Aware	3.80	0.713
Appeal	3.81	0.704
Ask	3.78	0.704
Act	3.85	0.713
Advocate	3.80	0.735

Source: Prepared by the researcher based on the Statistical Package for the Social Sciences (SPSS v26)

Measurement Model Assessment

The measurement model was assessed to establish the validity and reliability of the instruments measuring the independent variable, Data-Driven Decision-Making Perception (DDDM) and the dependent variable, consumer behavior according to the 5As model. Assessment included Outer Loadings to determine indicator–construct relationships and internal consistency and convergent validity using Cronbach's α, Composite Reliability (CR) and Average Variance Extracted (AVE). Discriminant validity was examined using the Fornell–Larcker and HTMT criteria to confirm construct distinctiveness. Finally, Collinearity–VIF was assessed to identify excessive overlap among variables and ensure model accuracy before structural relationship analysis.

Outer Loadings

Table 2 shows that all outer loadings exceeded the minimum acceptable threshold (0.70), confirming strong indicator representation of their latent constructs; no item required deletion.

Reliability and Validity of Latent Constructs

The results presented in the table on the reliability and validity of the latent variables indicate that all constructs of the (5As) Consumer Journey Model demonstrate high levels of reliability and consistency. The values of Cronbach's Alpha and Composite Reliability, including both rho_a and rho c, exceeded the scientifically accepted minimum threshold of 0.70, indicating strong internal consistency among the items measuring each construct (Table 3).

Furthermore, the Average Variance Extracted (AVE) values, all of which exceeded the threshold of 0.50, confirm the achievement of convergent validity. This reflects the ability of the indicators to explain a substantial proportion of the variance in the latent constructs they represent.

Discriminant Validity According to the HTMT and Fornell–Larcker Criteria

The results in Table 4 confirm discriminant validity among all latent variables, as all HTMT values were below the accepted threshold of 0.85. This indicates that each construct is conceptually distinct from the others, with no structural overlap between them, thereby confirming the model's suitability for proceeding with the assessment of structural relationships and the testing of the research hypotheses.

Table 2: Outer Loadings

item	Indicator	Loading Range
DQ	Q1 – Q4	0.776 – 0.829
DIT	Q5 – Q8	0.730 – 0.818
DCG	Q9 – Q12	0.756 – 0.831
DAL	Q13 – q16	0.770 – 0.786
BSA	Q17 – q20	0.758 – 0.838
Aware	Q21 – Q24	0.787 – 0.813
Appeal	Q25 – Q28	0.781 – 0.804
Ask	Q29 – Q32	0.771 – 0.816
Act	Q33 – Q36	0.798 – 0.808
Advocate	Q37 – Q40	0.773 – 0.840

Source: Prepared by the researcher based on Smart PLS 4.1.1.6 results

Table 3: Reliability and Validity of Latent Constructs

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Act	0.817	0.817	0.879	0.645
Advocate	0.831	0.835	0.887	0.664
Appeal	0.802	0.802	0.871	0.627
Ask	0.808	0.809	0.874	0.634
Aware	0.817	0.818	0.879	0.645

Source: Prepared by the researcher based on Smart PLS 4.1.1.6 results

Table 4: Discriminant Validity According to the HTMT Criterion

Parameters	Act	Advocate	Appeal	Ask	Aware	DDDM
Act	-	-	-	-	-	-
Advocate	0.665	-	-	-	-	-
Appeal	0.645	0.686	-	-	-	-
Ask	0.661	0.724	0.742		-	-
Aware	0.729	0.709	0.729	0.668	-	-
DDDM	0.753	0.769	0.777	0.757	0.795	-

Source: Prepared by the researcher based on Smart PLS 4.1.1.6 results

The results presented in Table 5 confirm discriminant validity according to the Fornell–Larcker criterion, as the square roots of the Average Variance Extracted (diagonal values) exceeded the correlation coefficients with the other constructs. This indicates that each latent variable represents a distinct and independent concept, thereby confirming the soundness of the model's conceptual structure and its suitability for structural analysis and hypothesis testing.

Collinearity Statistics (VIF)

The results of the inner-model VIF matrix show that all variance inflation factor values are below the statistically acceptable threshold (VIF<3), indicating no multicollinearity problem among the independent variables in the structural model (Table 6).

Structural Model Evaluation

Structural model evaluation focuses on assessing the strength of relationships among model variables and its overall fit. It includes the coefficient of determination (R^2) to estimate the variance in the dependent variable explained by the model, the effect size (f^2) to assess the strength of each independent variable's effect and Q^2 indicators to evaluate predictive accuracy. Finally, the Goodness of Fit (GOF) is considered as an overall criterion for assessing the model's fit to the data.

Coefficient of Determination (R^2)

According to Hair *et al*. R^2 values of 0.25, 0.50 and 0.75 indicate weak, moderate and high explanatory power, respectively. The study results show that R^2 values across the 5As stages ranged from 0.475 to 0.518, approaching the moderate level and indicating adequate explanatory power for behavioral research. The very high R^2 value for DDDM (0.999) reflects the strong integration of its constituent dimensions and their ability to explain the construct (Table 7).

Effect Size (f^2)

According to Cohen, f^2 values of 0.02, 0.15 and 0.35 indicate small, medium and large effects, respectively. The results show that DDDM has moderate to large effects across the 5As stages, with a very large effect on the Awareness stage (f^2 = 1.076), confirming the practical importance of data-driven decision-making in shaping consumer behavior (Table 8).

Model Fit

An SRMR value below 0.08 indicates good model fit. The SRMR values for the saturated and estimated models were 0.034 and 0.039, respectively, both well below the acceptable threshold, indicating good consistency between the model and the data with no substantial structural deviation (Table 9).

Table 5: Discriminant Validity According to the Fornell–Larcker Criterion

Parameter	Act	Advocate	Appeal	Ask	Aware	DDDM
Act	0.803	-	-	-	-	-
Advocate	0.550	0.815	-	-	-	-
Appeal	0.523	0.560	0.792	-	-	-
Ask	0.538	0.594	0.597	0.796	-	-
Aware	0.597	0.585	0.590	0.544	0.803	-
DDDM	0.681	0.703	0.696	0.681	0.720	1.000

Source: Prepared by the researcher based on SmartPLS 4.1.1.6 results

Table 6: VIF Matrix for the Inner Model

Parameter	Act	Advocate	Appeal	Ask	Aware	BSA	DAL	DCG	DDDM	DIT	DQ
Act	-	1.867	-	-	-	-	-	-	-	-	-
Advocate	-	-	-	-	-	-	-	-	-	-	-
Appeal	-	-	-	1.942	-	-	-	-	-	-	-
Ask	1.865			-	-	-	-	-	-	-	-
Aware	-	-	2.076	-	-	-	-	-	-	-	-
BSA	-	-	-	-	-	-	-	-	1.858	-	-
DAL	-	-	-	-	-	-	-	-	1.892	-	-
DCG	-	-	-	-	-	-	-	-	2.155	-	-
DDDM	1.865	1.867	2.076	1.942	1.000	-	-	-		-	-
DIT	-	-	-	-	-	-	-	-	1.832	-	-
DQ	-	-	-	-	-	-	-	-	1.978	-	-

Table 07: Results of the Coefficient of Determination

Parameter	R-square	R-square adjusted
Act	0.475	0.472
Advocate	0.503	0.501
Appeal	0.501	0.499
Ask	0.493	0.491
Aware	0.518	0.517
DDDM	0.999	0.999

Predictive Ability (Q^2 Predict)

The criterion that $Q^2 > 0$ indicates predictive ability. All Q^2 Predict values were positive and high, accompanied by low RMSE and MAE values, indicating that the model not only explains existing relationships but also has strong predictive ability for future consumer behavior (Table 10).

Model Goodness of Fit (GOF)

According to Tenenhaus *et al*. the most commonly used method for calculating GOF is the square root of the product of the average AVE and R^2. Its application yielded GOF ≈ 0.612, indicating good representational strength, as GOF > 0.36 is considered strong according to the adopted criteria.

Overall, the measurement model demonstrated strong factor loadings, high internal reliability and convergent validity, while discriminant validity was confirmed without multicollinearity issues. The structural model also showed adequate explanatory power, meaningful effect sizes, good model fit and strong predictive ability, supporting its suitability for hypothesis testing and achieving the study objectives.

Testing of Sub-Hypotheses

According to the results presented in Table 11, all hypotheses are supported ($p < 0.001$, $T > 1.96$), with strong positive effects. All relationships between the independent variable, Data-Driven Decision Making (DDDM) and the different stages of the 5As model were statistically significant and positive, as indicated by the very high T-statistics and P-values below the accepted significance level. These findings support all hypotheses concerning the influence of data-driven decision making on consumer awareness, message appeal, inquiry, action and product advocacy, confirming the practical importance of DDDM in shaping consumer behavior.

Table 8: Effect Size Results

Parameter	Act	Advocate	Appeal	Ask	Aware	BSA	DAL	DCG	DDDM	DIT	DQ
Act	-	0.019	-	-	-	-	-	-	-	-	-
Advocate	-	-	-	-	-	-	-	-	-	-	-
Appeal	-	-	-	0.058	-	-	-	-	-	-	-
Ask	0.019	-	-	-	-	-	-	-	-	-	-
Aware	-	-	0.033	-	-	-	-	-	-	-	-
BSA	-	-	-	-	-	-	-	-	34.358	-	-
DAL	-	-	-	-	-	-	-	-	31.234	-	-
DCG	-	-	-	-	-	-	-	-	30.149	-	-
DDDM	0.352	0.405	0.307	0.269	1.076	-	-	-	-	-	-
DIT	-	-	-	-	-	-	-	-	32.755	-	-
DQ	-	-	-	-	-	-	-	-	31.962	-	-

Source: Prepared by the researcher based on Smart PLS 4.1.1.6 results

Table 9: Model Fit Results

Parameter	Saturated model	Estimated model
SRMR	0.034	0.039
d_ULS	1.017	1.326
d_G	n/a	n/a
Chi-square	∞	∞
NFI	n/a	n/a

Source: Prepared by the researcher based on SmartPLS 4.1.1.6 results

Table 10: Results of Predictive Ability (Q^2 Predict)

Parameter	Q^2predict	RMSE	MAE
DDDM	0.999	0.034	0.027
Aware	0.515	0.699	0.555
Appeal	0.483	0.722	0.566
Ask	0.463	0.736	0.584
Act	0.461	0.737	0.588
Advocate	0.493	0.715	0.566

Source: Prepared by the researcher based on Smart PLS 4.1.1.6 results

Table 11: Results of Testing the Effects of Data-Driven Decision-Making (DDDM) on the Stages of the 5As Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
DDDM -> Aware	0.720	0.720	0.021	33.986	0.000
DDDM -> Appeal	0.563	0.563	0.044	12.761	0.000
DDDM -> Ask	0.515	0.514	0.039	13.158	0.000
DDDM -> Act	0.588	0.586	0.043	13.694	0.000
DDDM -> Advocate	0.613	0.613	0.040	15.285	0.000

Hypothesis 1 (H1)

Effect of Data-Driven Decision Making on Awareness DDDM → Aware Data-Driven Decision Making, through its various dimensions (DQ – Data Quality, DIT–Data Infrastructure and Technology, DCG – Data Culture and Governance, DAL – Data Analytical Literacy and BSA–Business Strategy Alignment), enables organizations to reach international digital consumers more effectively. In the digital environment, data facilitates the personalization of marketing messages across international digital channels, including social media, targeted advertising and global consumer behavior analytics.

Theoretically, the Awareness stage represents the starting point of the consumer journey within the 5As model. Enhancing awareness through data enables organizations to improve consumers' recognition and perception of the brand and its marketing messages.

- The hypothesis is strongly supported. Data-Driven Decision Making enhances consumers' awareness of the brand within the international digital environment, with a positive contribution from all dimensions of DDDM

Hypothesis 2 (H2)

The Effect of Data-Driven Decision Making on Consumer Appeal DDDM → Appeal.

By using the dimensions of Data-Driven Decision Making, organizations can design appealing marketing content that aligns with the preferences of international digital consumers. Data enables firms to analyze previous responses and consumers' emotional interactions and identify the messages that are most influential for each audience. Theoretically, the Appeal stage focuses on highlighting product benefits in ways that attract consumers, while data analysis enhances the effectiveness of personalized digital messages across international channels.

- The hypothesis is supported; Data-Driven Decision Making enhances consumer appeal and increases consumers' initial engagement in the digital environment, with strong support across the five dimensions of data-driven decision making.

Hypothesis 3 (H3)

The Effect of Data-Driven Decision Making on the Ask/Search Stage DDDM → Ask

In the international digital environment, the dimensions of Data-Driven Decision Making enable consumers to access accurate information and intelligent product comparisons. Predictive analytics and personalized recommendations facilitate information gathering and quality verification, thereby supporting the Ask stage in the 5As model, where consumers search for product features and benefits before making a decision.

- The hypothesis is supported; Data-Driven Decision Making enhances the ability of international digital consumers to search and verify information, with a positive effect across all dimensions of Data-Driven Decision Making.

Hypothesis 4 (H4)

The Effect of Data-Driven Decision Making on the Act Stage DDDM → Act

Data-Driven Decision Making strengthens the Act stage, involving purchase or actual decision-making, by providing international digital consumers with a smooth purchasing experience based on accurate data. Dimensions of Data-Driven Decision Making, such as DAL and BSA, contribute to providing intelligent recommendations and personalized offers, while DIT and DCG ensure technological integration and governance of digital transactions, thereby reducing perceived risks and increasing consumer trust.

- The hypothesis is strongly supported; Data-Driven Decision Making enhances purchase intention and the experience of international digital consumers, with a positive effect across all dimensions of Data-Driven Decision Making

Hypothesis 5 (H5)

The Effect of Data-Driven Decision Making on the Advocate Stage DDDM → Advocate

The Advocate stage is based on loyalty and brand recommendation. Data-Driven Decision Making contributes to creating an integrated and personalized experience that encourages international digital consumers to promote products through social networks and international digital platforms. Accordingly, Data-Driven Decision Making enables organizations to transform consumers into active brand advocates, thereby strengthening brand reputation and digital reach.

- The hypothesis is strongly supported; Data-Driven Decision Making enhances loyalty and recommendation behaviors in the international digital environment, with all dimensions of Data-Driven Decision Making contributing positively

Testing the Main Hypothesis

To address the main hypothesis, the analysis focuses on the sequential relationships within the 5As model, where this sequence represents the flow of consumer behavioral dynamics. Based on the Path Coefficients results, the direct sequential paths connecting the different stages are presented along with their statistical indicators, including β for the coefficient, T for the statistical value and P for significance.

These relationships indirectly support the main hypothesis by demonstrating the flow of influence across the different stages without aggregating them into a single indicator for the main hypothesis.

The results show that all sequential paths are statistically significant ($p < 0.05$, $T > 1.96$), confirming the flow of consumer behavior across the different stages. For example, Awareness (Aware) enhances Appeal with a coefficient of 0.185 and this flow continues through to the Advocate stage.

This indirectly supports the main hypothesis through the sequential relationships. Accordingly, the main hypothesis is supported, as Data-Driven Decision Making enhances each stage of the international digital consumer journey within the 5As model, beginning with Awareness and ending with Advocacy, with the influence continuing across all stages.

These findings demonstrate that Data-Driven Decision Making and its five dimensions in the international digital environment are not limited to stimulating purchase behavior, but contribute to shaping an integrated and interconnected consumer experience that begins with awareness and ultimately drives loyalty and recommendation.

CONCLUSION

In the era of accelerating digital transformation, where digital marketing is expanding globally and reshaping consumer–brand interactions, Data-Driven Decision Making (DDDM) has become essential for understanding and improving consumer behavioral dynamics across cultural and geographical boundaries. This study provides a theoretical and empirical contribution by examining how DDDM influences the digital consumer journey, using the 5As model as an integrated analytical framework and focusing on its five dimensions: Data Quality (DQ), Data Infrastructure and Technology (DIT), Data Culture and Governance (DCG), Data Analytical Literacy (DAL) and Business Strategy Alignment (BSA). The findings reveal that DDDM extends beyond improving operational efficiency to reshaping the consumer journey in ways that strengthen trust, loyalty and sustained engagement in international digital environments.

Theoretically, the study confirms that DDDM serves as a bridge between traditional consumer behavior theory and the contemporary digital reality. It enhances the Awareness (Aware) stage through high-quality data (DQ) and advanced analytics (DAL), generating accurate recommendations that reduce digital noise and strengthen non-random awareness. It also supports the transition to Appeal through integrated technology (DIT), which enables personalized content capable of stimulating emotional responses. During the Ask and Act stages, Data Governance (DCG) plays a central role in strengthening trust through transparency and compliance with ethical standards, reducing privacy barriers and encouraging repeated purchases. At the Advocate stage, DDDM demonstrates its ability to transform consumers into digital brand advocates, supported by Business Strategy Alignment (BSA), thereby strengthening long-term loyalty and contributing to brand growth through international social networks.

The findings further demonstrate that DDDM positively and significantly enhances every stage of the 5As model, explaining a substantial proportion of the variance in consumer behavior. The sequential relationships (Aware → Appeal → Ask → Act → Advocate) reveal an interconnected flow that reflects the dynamic nature of the digital consumer journey. DDDM facilitates smooth transitions between these stages through accurate data and ethical analytics. These findings provide practical evidence for marketing managers regarding the need to integrate DDDM into their strategies, particularly in international markets characterized by diverse consumer behaviors, enabling higher returns and lower costs through intelligent personalization.

In conclusion, this study confirms that DDDM is not merely a technological tool, but a strategic driver that reshapes the digital consumer journey toward a more efficient and sustainable experience. This perspective opens new avenues for research at the intersection of digital marketing and artificial intelligence in the digital era.

Recommendations

- **Investing in Data Quality and Analytics:** Ensure high Data Quality (DQ), adopt advanced analytical technologies (DAL) and establish effective Data Governance (DCG) to generate accurate and reliable insights.
- **Personalizing Digital Marketing Messages:** Use DDDM analytics to design attractive, interactive and responsive marketing campaigns that reflect international cultural preferences.
- **Empowering Digital Consumers to Make Informed Decisions:** Provide digital tools for comparing products and verifying their quality across multiple platforms, while leveraging data to reduce perceived risks.
- **Strengthening International Digital Loyalty and Advocacy:** Design personalized consumer experiences that create emotional engagement and encourage consumers to recommend products and share positive experiences.

- **Directing Future Research toward Multidimensional and Cross-Cultural Analysis:** Examine the integrated effects of DDDM dimensions on digital consumer behavior across different international environments to develop effective and sustainable international marketing strategies

REFERENCES

1. Rajan, P. "Integrating IoT analytics into marketing decision making: A smart data-driven approach." *International Journal of Data Informatics and Intelligent Computing*, vol. 3, no. 1, 2024, pp. 12–22. https://doi.org/10.59461/ijdiic.v3i1.92.
2. Shah, D. and B. Murthi. "Marketing in a data-driven digital world: implications for the role and scope of marketing." *Journal of Business Research*, vol. 125, 2021, pp. 772–779. https://doi.org/10.1016/j.jbusres.2020.06.062.
3. Nordin, F. and A. Ravald. "The making of marketing decisions in modern marketing environments." *Journal of Business Research*, vol. 162, 2023, article 113872. https://doi.org/10.1016/j.jbusres.2023.113872.
4. Cristofaro, M. *et al*. "Growth hacking: A scientific approach for data-driven decision making." *Journal of Business Research*, vol. 186, 2025, article 115030. https://doi.org/10.1016/j.jbusres.2024.115030.
5. Sleep, S. *et al*. "Removing silos to enable data-driven decisions: The importance of marketing and it knowledge, cooperation and information quality." *Journal of Business Research*, vol. 156, 2023, article 113471. https://doi.org/10.1016/j.jbusres.2022.113471.
6. Latino, M. *et al*. "Surfing twin transition in agri-food supply chains: The role of IOT and data analytics in sustainable decision-making." *Journal of Industrial Information Integration*, vol. 48, 2025, article 100983. https://doi.org/10.1016/j.jii.2025.100983.
7. Arunachalam, D. and N. Kumar. "Benefit-based consumer segmentation and performance evaluation of clustering approaches: Evidence of data-driven decision-making." *Expert Systems with Applications*, vol. 111, 2018, pp. 11–34. https://doi.org/10.1016/j.eswa.2018.03.007.
8. Cruz, R. and A. Rosário. "Data-driven decision-making in marketing: A systematic literature review of emerging themes and research gaps." *Systematic Review*, vol. 13, no. 12, 2025, pp. 1114.
9. Cao, Y. *et al*. "Analyzing adoption factors of data-driven nudging for e-commerce platforms using an integrated decision model." *Electronic Commerce Research and Applications*, vol. 71, 2025, article 101500. https://doi.org/10.1016/j.elerap.2025.101500.
10. Wu, P. *et al*. "Multi-source data driven decision-support model for product ranking with consumer psychology behavior." *Information Fusion*, vol. 118, 2025, article 103014. https://doi.org/10.1016/j.inffus.2025.103014.
11. Wachwanakijkul, P. *et al*. "Data-driven approaches to predicting customer churn in a non-contractual car-sharing company." *Transportation Research Interdisciplinary Perspectives*, vol. 33, 2025, article 101600. https://doi.org/10.1016/j.trip.2025.101600.
12. Miedema, E. *et al*. "Towards trustworthy artificial intelligence for decision-making: A lifecycle perspective on knowledge- and data-driven artificial intelligence systems." *Computers in Industry*, vol. 174, 2026, article 104409. https://doi.org/10.1016/j.compind.2025.104409.
13. Cho, H. *et al*. "Data-driven component-level decision-making for online remanufacturing of gas-insulated switchgear." *CMES—Computer Modeling in Engineering and Sciences*, vol. 145, no. 2, 2025, pp. 1941–1967. https://doi.org/10.32604/cmes.2025.072455.
14. Rosario, A. and J. Dias. "How has data-driven marketing evolved: Challenges and opportunities with emerging technologies." *International Journal of Information Management Data Insights*, vol. 3, no. 2, 2023, article 100203.
15. Nechita, R.-M. *et al*. "Identifying and prioritising factors for effective decision-making in data-driven organisations: A DEMATEL approach." *Systems*, vol. 13, no. 8, 2025, article 687.
16. Smith, R. and E. Wilson. "Introduction to the Special issue on data quality in survey research." *Journal of Marketing Theory and Practice*, vol. 33, no. 1, 2025, pp. 1–2.
17. Lee, J. and Y. Dai. "Artificial intelligence and data-driven technology in the public policy cycle: Comparative applications, opportunities and risks." *Journal of Comparative Policy Analysis*, vol. 27, nos. 5–6, 2025, pp. 477–493. https://doi.org/10.1080/13876988.2025.2598371.
18. Bozkurt, Y. *et al*. "Assessing data governance models for smart cities: Benchmarking data governance models on the basis of European Urban requirements." *Sustainable Cities and Society*, vol. 130, 2025, article 106528. https://doi.org/10.1016/j.scs.2025.106528.
19. Ben Miloud, M. "Digital intelligence and agile governance: How ICT catalyzes competitiveness. case study: Siemens and alstom." *International Journal of Economic Performance*, vol. 8, no. 1, 2025, pp. 383–399.
20. Szukits, Á. and P. Móricz. "Towards data-driven decision making: The role of analytical culture and centralization efforts." *Review of Managerial Science*, vol. 18, 2024, pp. 2849–2887. https://doi.org/10.1007/s11846-023-00694-1.

21. Lezghed, A. *et al*. "A Bibliometric Perspective on the Relationship Between Artificial Intelligence and Digital Culture." *International Journal of Economic Performance*, vol. 8, no. 2, 2025, pp. 371–389.
22. Nwagwu, W. "Citation Analysis of Global Research on Data Literacy." *Education and Information Technologies*, vol. 30, 2025, pp. 15931–15959. https://doi.org/10.1007/s10639-025-13397-9.
23. Ncube, M. and P. Ngulube. "Enhancing Environmental Decision-Making: A Systematic Review of Data Analytics Applications in Monitoring and Management." *Discover Sustainability*, vol. 5, no. 290, 2024, pp. 1–21. https://doi.org/10.1007/s43621-024-00510-0.
24. Gopal, P. *et al*. "Impact of Big Data Analytics on Supply Chain Performance: An Analysis of Influencing Factors." *Annals of Operations Research*, vol. 333, 2024, pp. 769–797. https://doi.org/10.1007/s10479-022-04749-6.
25. Shamim, S. *et al*. "Rapid Innovation Management Capability and Crisis-Driven Business Model Innovation Performance: Roles of Strategic-IT-Alignment and Operational-IT-Effectiveness." *Journal of Business Research*, vol. 193, 2025, p. 115358. https://doi.org/10.1016/j.jbusres.2025.115358.
26. Benalia, F. "The Digital Technologies That Contribute to the Fourth Industrial Revolution and Gains of Using Supply Chains in an Economic Institution." *International Journal of Economic Performance*, vol. 6, no. 2, 2023, pp. 408–426.
27. Zhang, J. and C.-W. Chang. "Consumer Dynamics: Theories, Methods and Emerging Directions." *Journal of the Academy of Marketing Science*, vol. 49, no. 1, 2021, pp. 166–196. https://doi.org/10.1007/s11747-020-00720-8.
28. Gowrisankaran, G. and M. Rysman. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy*, vol. 120, no. 6, 2012, pp. 1173–1219. https://www.jstor.org/stable/10.1086/669540.
29. Gopalakrishnan, A. *et al*. "Consumer Dynamic Usage Allocation and Learning Under Multipart Tariffs." *Marketing Science*, vol. 34, no. 1, 2015, pp. 116–133. https://doi.org/10.1287/mksc.2014.0877.
30. Gerunov, A. "Dynamics of Consumer Inflation with Irrational Expectations and Exogenous Economic Shocks." *Argumenta Oeconomica*, vol. 55, no. 2, 2025, pp. 112–132. https://doi.org/10.15611/aoe.2025.2.08.
31. Boussair, B. "AI Marketing and Its Role in Enhancing E-Commerce within Economic Enterprises: An Analytical Study of Tesla's Experience (2012–2024)." *International Journal of Economic Performance*, vol. 8, no. 1, 2025, pp. 228–247.
32. Senayah, W. *et al*. "Using the AIDA Model to Predict Consumer Behaviour: The Moderating Effect of Brand Evangelism." *SN Business & Economics*, vol. 5, no. 168, 2025, pp. 1–23. https://doi.org/10.1007/s43546-025-00938-0.
33. Polat, E. "Creating Loyal Customers with Digital." *Handbook of Technology Application in Tourism in Asia*, edited by A. Hassan, Springer, 2022, pp. 257–271. https://doi.org/10.1007/978-981-16-2210-6.
34. Affan, N. *et al*. "The Influence of the 5A Customer Path on Online Purchasing Decisions (Case Study: 3SECOND Kuningan)." *Indonesian Journal of Business Analytics*, vol. 5, no. 3, 2025, pp. 2543–2554. https://doi.org/10.55927/ijba.v5i3.14684.
35. Mas'adi, M. *et al*. "Instagram Customer Behavior Pattern Connectivity Based on Customer Path 5A Advocacy in Purchasing Decision Making." *Budapest International Research and Critics Institute-Journal*, vol. 5, no. 1, 2022, pp. 7820–7828. https://doi.org/10.33258/birci.v5i1.4527.
36. Rafiq, M. *et al*. "Analysis of the Advertising Effectiveness of the Management Study Program of the Darmajaya Institute of Informatics and Business through Instagram with an Approach Customer Response Index (CRI)." *Jurnal Ekonomi*, vol. 13, no. 4, 2024, pp. 83–91. https://doi.org/10.54209/ekonomi.v13i04.
37. Rodrigues, M. "The Relevance of Social Listening in the Different Stages of the Consumer Journey." *NOVA Information Management School, Universidade Nova de Lisboa*, 2023.
38. Rodríguez Salazar, M. "Omnichannel Marketing Model Applied at the Shopping Centers in Medellín City." *Mercados y Negocios*, vol. 23, no. 46, 2022, pp. 31–56. https://doi.org/10.32870/myn.vi46.7662.g6737.
39. Purnomo, A. "Social Factors and Social Media Usage Activities on Customer Path 5A Continuity Due to E-Marketing Communication." *International Journal of Social Science and Business*, vol. 7, no. 1, 2023, pp. 11–24. https://doi.org/10.23887/ijssb.v7i1.46701.
40. Hwang, J. and J.-y. Kim. "Food Tourists' Connectivity through the 5A Journey and Advocacy: Comparison between Generations Y and X." *Asia Pacific Journal of Tourism Research*, vol. 25, no. 1, 2020, pp. 27–38. https://doi.org/10.1080/10941665.2019.1580756.